Journal of Harbin Engineering University
ISSN: 1006-7043

Vol 44 No. 10
October 2023

Talent Evaluation Model for College Students Based on Big Data Technology

Dan Nie

School of Nursing, Xinyang Vocation and Technical College, Xinyang 464000, China

Abstract: In order to improve the evaluation effect of college students' comprehensive quality, this paper combines big data technology to build a college student talent evaluation model, proposes a bilingual LDA model that integrates college students' evaluation characteristics, and completes the construction of the model. Moreover, this paper proposes the specific process of normative comparison, and conducts the comparison experiment and result analysis of normative comparison according to the process. Finally, this paper evaluates the results of each comparison process and compares it with the bilingual LDA model without word features to prove the effectiveness of the comparison model and comparison process constructed in this paper. The experimental analysis shows that the college student talent evaluation model based on big data technology proposed in this paper can effectively improve the effect of college student talent evaluation.

Keywords: big data; college students; talents; evaluation model

1 Introduction

With the continuous development of the world economy, the demand for talents by various enterprises, institutions and government agencies is constantly increasing, and the quality requirements for talents are also constantly improving. The essence of the competition between countries, such as economic competition, scientific and technological competition, military competition, social and cultural competition, etc., is the competition between talents. Only talents can promote the development of national economy, society and military science and technology. As a country with a large population, the labor resources are very rich, but it does not mean that the human resources are rich. There has always been a low-quality population, a lack of high-quality talents, and a lack of high-precision talents. Therefore, enterprises, institutions and government agencies must pay attention to the development and utilization of talents, and establish the employment concept of "making the best use of their talents" [1].

In order to better cope with the increasing uncertainties in the world economy and the challenges posed by various new technologies and technologies, enterprises must pay attention to human resource management, stimulate the potential of employees, improve their quality and give full play to their talents. Making the best of people is an important driving force for enterprises to promote their sustainable development and improve their competition [2]. Enterprises need to pay attention to the construction of enterprise informatization while paying attention to talent development, carrying out talent strategy and establishing and improving talent system. Enterprise informatization is not only a reminder of enterprise efficiency, but also a change of management mode, which will ultimately play a decisive role in enterprise management mode and enterprise brand [3]. Based on the above factors, various enterprises and experts have begun to explore the talent quality evaluation system, which focuses on the informatization of talent evaluation. Through this system, rapid changes can be brought to various aspects of human resources such as enterprise recruitment, professional title system development, career development and salary performance training, effectively improving the corresponding quality of enterprise employees and improving employee satisfaction in the enterprise.

The great role of knowledge in society, especially in enterprises, has gradually emerged. Because of the uniqueness of implicit knowledge, it is difficult to copy and unspeakable. Therefore, the research on implicit knowledge based on individuals has become the object of concern for organizations and individuals. This paper starts with the meaning of implicit knowledge, summarizes the classification, structure, acquisition and dissemination of implicit knowledge, and does a good job of basic work for the next step. Since the concept of competency was put forward, the research on competency has become the global focus [4]. Competency is a potential and deep level characteristic that can distinguish excellent performers from ordinary performers. As the backbone of enterprises and other organizations, managers are the key to influencing organizational performance. Studying their knowledge structure to evaluate the quality of talents is also a summary of their competency. However, the current research focuses on organization and performance, while the implicit knowledge structure of managers in talent evaluation is less [5]. Implicit knowledge is closely related to the individual of cognition and behavior, with a high degree of subject dependence. It is gradually refined by the subject consciously or unconsciously in certain roles and tasks. Therefore, it is necessary to systematically study the implicit knowledge and structure of agents based on roles and tasks. Managers are the main supporters of organizational development and innovation, guides the direction of development in the organization, and intermediaries connecting leaders and employees. Their role cannot be underestimated. The key to study managers is to study their knowledge structure and ability. Managers' work style and knowledge structure directly affect their work effect and efficiency. Managers' knowledge structure is a prerequisite for managers to complete tasks and improve performance [6]. Therefore, ability and knowledge structure, and performance are both external and internal. Competence and quality are the internal conditions and basis of performance and development, and the expression of knowledge structure, while knowledge structure is the internal accumulation of ability and quality [7]

Scholars classify implicit knowledge according to the degree to which it can be realized or expressed and explicit. On the basis of experiments, literature [8] divided implicit knowledge into "unconscious knowledge", "knowledge that can be realized but cannot be expressed through words" and "knowledge that can be realized and can be expressed through words". Implicit knowledge can be divided into expressible implicit knowledge and non expressible implicit knowledge. This shows that there is no obvious boundary between implicit knowledge and explicit knowledge, and the two are just "degrees". Literature [9] classifies implicit knowledge into three categories: representational, grey and whitened implicit knowledge according to the carrier's cognition of implicit knowledge description object and the explicit degree of implicit knowledge, combined with its formation process. Each layer is the deepening of the previous layer. The implicit knowledge of people's appearances only stays in experience and imitation. The gray implicit knowledge is still scattered, and the whitened implicit knowledge is relatively systematic, realizing the truth cognition of regularity. Literature [10] divides knowledge into four categories: full implicit knowledge, semi implicit knowledge, semi explicit knowledge and full explicit knowledge, in which full implicit knowledge mainly refers to mental models, ways of thinking and solving problems and experiences; Semi tacit knowledge refers to clear ideas, knowledge, procedures and skills; Semi explicit knowledge is the dominance of expressing ideas in a small scope; Full explicit knowledge refers to the systematization, standardization and unification of knowledge, which can be shared, widely used and evaluated.

Today's world economy is more closely linked. Enterprises should not only face the competition from domestic peers, but also from the world[11]. How to own and reserve talents that meet the requirements of the enterprise, how to make rational and effective use and allocation of talents, and how to make them be used by the enterprise and give full play to the benefits, this requires a scientific and reasonable evaluation mechanism to select and evaluate outstanding talents that match the enterprise [12]. In order to meet the above requirements, it is necessary to "know people" first, and then "do well". The key is that as a manager of an enterprise, you should fully understand what employees can do and what they are good at, and clearly know what skills and qualities are required for specific positions, and then assign the right employees to the right positions to achieve the optimal matching between employees and positions, so as to further help employees and the enterprise achieve a win-win situation [13]. And talent evaluation is just the key means and method to effectively understand the characteristics of employees and realize the match between people and posts. For talent evaluation, many scholars and research institutions have conducted research from different perspectives [14] Literature [15] compiled a competency assessment scale, which mainly includes five dimensions: leadership, cooperation, coordination, learning ability and personality characteristics. The research object is senior professional managers. The scale has achieved good practical results in the process of practical application. Literature [16] defined the research goal as middle managers and built a competency model, which mainly includes: ability, personality, IQ and motivation. The AHP method was used to give weight to indicators to facilitate the scientific and quantitative evaluation of middle managers. Du Yong, Du Jun, Literature [17] took the staff in e-commerce industry as the research object, extracted their common quality characteristics, and built a quality evaluation system, which provided favorable value for the future human resource evaluation of the industry and improved the efficiency of human resource management. Bu Jinwen, Literature [18] took librarians in many universities as research objects, analyzed their common quality characteristics, and constructed talent evaluation indicators that include three dimensions: professional basis, personality characteristics, and dedication. This evaluation system has played a guiding role in the recruitment, enrollment, assessment and training of librarians.

This paper combines big data technology to build a college student talent evaluation model, which provides a reference for schools to better cultivate talents, and also provides a channel for the society to select talents.

2 Research on the comparison method of requirements and specifications of talent evaluation system

2.1 Construction of comparable corpus in the field

of talent evaluation

In order to construct a comparable corpus for talent evaluation, the paper firstly aligns Chinese and English terms for talent evaluation.

(1) Word frequency. In the evaluation text, the word frequency of the terms in each language is counted separately, and the word frequency ratios of the two language terms are largely in a corresponding relationship.

$$f_1(term_c) = \frac{N_{term_c}}{N_c} \quad (1)$$

$$f_1(term_e) = \frac{N_{term_e}}{N_e} \quad (2)$$

(2) Co-occurrence characteristics. In the evaluation text, there is a certain consistency in the co-occurrence frequency of terms that can be aligned. In aligned sentences, the higher the frequency of co-occurrence, the more likely it is to be an alignable term. The co-occurrence features are expressed as follows:

$$f_2\left(term_c \mid term_e\right) = \frac{N\left(term_c term_e\right)}{N\left(term_e\right)} \quad (3)$$

Since the evaluation text of the practice data is selected, only the probability of the occurrence of the educational data terms under the condition of the practice data terms is calculated.

This paper combines the above two features to complete bilingual term alignment. The specific process is:

(1) The algorithm combines the ETCS talent evaluation system requirements specification evaluation texts into Chinese-English aligned texts, $\left\{(S_{C1}, S_{E1}), (S_{C2}, S_{E2}), \ldots, (S_{Ci}, S_{Ei}), \ldots, (S_{Cn}, S_{En})\right\}$, where C and E represent educational data texts and practice data texts, respectively.

(2) The algorithm selects the terms in the talent evaluation practice data term dictionary constructed in the third chapter of the thesis in turn, finds the sentences in which the practice data term $terme_e$ appears, lists the corresponding educational data sentence set $\left\{S_{Ct_1}, S_{Ct_2}, \ldots, S_{Ct_n}\right\}$, and counts the total number $N(term_e)$ of occurrences of the term $terme_e$, and calculates the word frequency $f_1(\ \ termm_e)$.

(3) The algorithm extracts the educational data terms that appear in the sentence set $\left\{S_{Ct_1}, S_{Ct_2}, \ldots, S_{Ct_n}\right\}$ as candidate terms, calculates the number $N(termc_i)$ of occurrences of each candidate educational data term, and obtains the co-occurrence feature $f_2(term_{c_i} \mid term_e)$ of each candidate educational data term and practice data term.

(4) The algorithm calculates the Dice coefficient according to formula (4), and selects the maximum coefficient value as the aligned educational data term of the practice data term.

$$dice = \frac{f_2\left(term_{c_i} / term_e\right)}{f_1\left(term_{c_j}\right) * f_1\left(term_e\right)} \quad (4)$$

The construction process of comparable corpus for talent evaluation is shown in Figure 1.

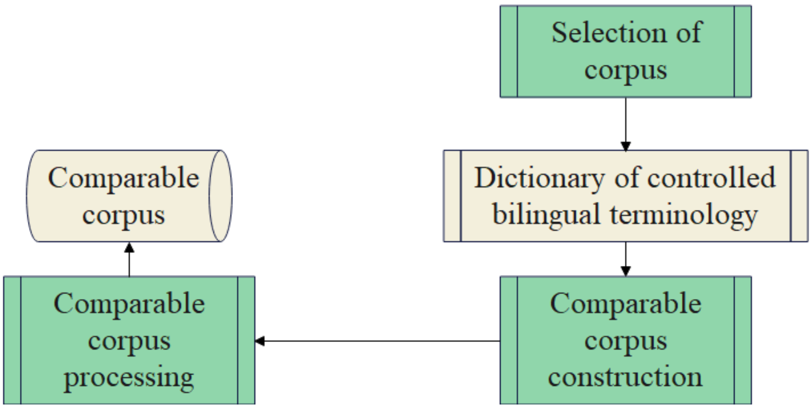


Figure 1 Construction process of comparable corpus for talent evaluation

2.2 Comparison model of specification differences of system requirements

In view of the advantages of the LDA model in processing short texts and its high semantic representation, combined with the characteristics of the normative texts for talent evaluation, the paper uses the LDA model as the text representation model. The probabilistic graphical model of the LDA model is shown in Figure 2.

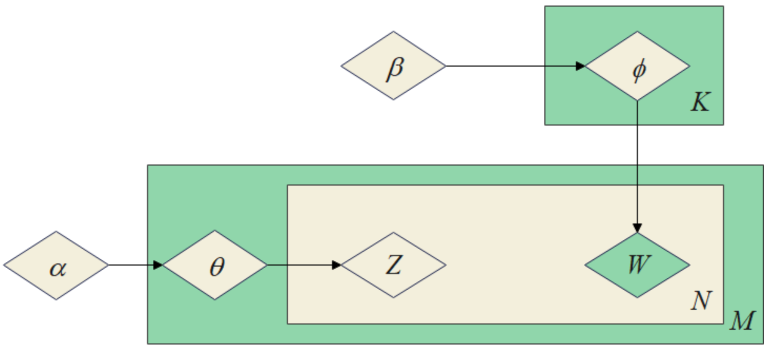


Figure 2 LDA model diagram

The variables in the shaded part of the LDA model diagram are represented as observables, θ is an M*K matrix, $\vec{\theta}_m$ is the topic distribution of the m-th article,where $\vec{\theta}_m \sim Dir(\vec{\alpha});\beta$ is the parameters of the prior Dirichlet distribution of the topic distribution of each document, where $\vec{\varphi}_k \sim Dir(\vec{\beta});w$ is the observed words; z are the topics implicitly assigned to each observed word.

The process is summarized in two steps:1) $\vec{\alpha} \rightarrow \vec{\theta}_m \rightarrow z_{m,n};2)\vec{\beta} \rightarrow \vec{\varphi}_k \rightarrow \omega_{m,n}$. Step 1) is $p(\vec{z})$, and step 2) is $p(\vec{w}\,|\,\vec{z})$. According to the conditional probability formula, we get:

$$p(\vec{w},\vec{z}) = p(\vec{w}\,|\,\vec{z})p(\vec{z}) \quad (5)$$

The goal of LDA is to find out the themes implied by each word, namely:

$$p(\vec{z}\,|\,\vec{w}) = \frac{p(\vec{w},\vec{z}))}{\sum_{z} p(\vec{w},\vec{z})} \quad (6)$$

In the LDA model, α and β are a priori parameters set based on experience, and there is only w in the model, and the hidden variables θ and φ are estimated using GibbsSampling sampling. The joint probability generated by the entire training corpus is as follows:

$$p(\vec{w},\vec{z}\mid\vec{\alpha},\vec{\beta})=p(\vec{w}\mid\vec{z},\vec{\beta})p(\vec{z}\mid\vec{\alpha}) \quad (7)$$

$p(\vec{z}\mid\vec{\alpha})$ has the following formula:

$$p(\vec{z}\mid\vec{\alpha})=\frac{\Delta(\vec{n}+\vec{\alpha})}{\Delta(\vec{\alpha})} \quad (8)$$

The topic corresponding to the i-th word in the corpus $\vec{z}$ is denoted as z_i, and $\neg i$ means to remove the i-th word. According to the GibbsSampling algorithm, for the nth word of the mth document, there is the following formula:

$$p\left(z_i=k\mid\vec{w},\vec{z}_{\neg i}\right)\propto p\left(z_i=k,w_i=t\mid\vec{w}_{\neg i},\vec{z}_{\neg i}\right) \quad (9)$$

The (z_i, w_i) corresponding to the i-th word is removed from the above formula, and the posterior distributions of $\overrightarrow{\theta_m}$ and $\vec{\varphi}_k$ are both Dirichlet distributions.

$$p\left(\vec{\theta}_m\mid\vec{z}_{\neg i},\vec{w}_{\neg i}\right)=Dir\left(\vec{\theta}_m\mid\vec{n}_{m,\neg i},\vec{\alpha}\right) \quad (10)$$

$$p\left(\vec{\varphi}_k\mid\vec{z}_{\neg i},\vec{w}_{\neg i}\right)=Dir\left(\vec{\varphi}_k\mid\vec{n}_{m,\neg i},\vec{\beta}\right) \quad (11)$$

The Gibbs sampling formula is as follows:

$$p\left(z_i=k\mid\vec{z}_{\neg i},\vec{w}\right)\propto\frac{n_{m,\omega_{\neg i}}^{k}+\alpha_k}{\sum_{k=1}^{K}\left(n_{m,\neg i}^{k}+\alpha_k\right)}\cdot\frac{n_{k,\omega_{\neg i}}^{v}+\beta_v}{\sum_{v=1}^{V}\left(n_{k,\neg i}^{v}+\beta_v\right)} \quad (12)$$

The LDA method mentioned above is a text representation model, which represents text as a vector with its features. Common distance measurement methods are as follows:

(1) Euclidean distance: It refers to calculating the distance between two vectors. The closer the distance, the more similar the Euclidean distance.

$$D(\mathrm{x},\mathrm{y})=\sqrt{\sum_{i=1}^{n}\left(x_i-y_i\right)^2} \quad (13)$$

(2) Cosine similarity: It calculates the angle between two vectors, and the smaller the angle is, the more similar the cosine similarity is.

$$D(\mathrm{x},\mathrm{y})=\frac{\sum_{i=1}^{n}x_iy_i}{\sqrt{\sum_{i=1}^{n}x_i^2\sum_{i=1}^{n}y_i^2}} \quad (14)$$

(3) Jaccard similarity coefficient: it refers to the proportion of the intersection elements of the two sets in the union of the two sets.

$$D(\mathrm{x},\mathrm{y})=\frac{\sum_{i=1}^{n}x_iy_i}{\sum_{i=1}^{n}x_i^2+\sum_{i=1}^{n}y_i^2-\sum_{i=1}^{n}x_iy_i} \quad (15)$$

Figure 3 is a graph showing the probability of bilingual LDA. In the figure, C and E represent the specifications of CTCS and ETCS, respectively, φ^C and φ^E represent the word distribution of the ETCS and CTCS normative document sets, respectively, k represents the topic number, φ_k^C and φ_k^E represent the probability distribution of the terms contained in the topic k, which is a V-dimensional vector.

The topic distributions in documents d^C and

d^{E} are denoted as $Z_{m,n}^{C}$ and $Z_{m,n^{E}}^{E}$, respectively, which are the topics of the term n^{C} or n^{E} in the m-th document pair. The observed terms in documents d^{C} and d^{E} are $\omega_{m,n}^{C}c$ and $\omega_{m,n^{E}}^{E}$ representing the nth term in the m-th document pair, which comes from a fixed vocabulary. N^{C} and N^{E} represent the total number of words in documents d^{C} and d^{E}.

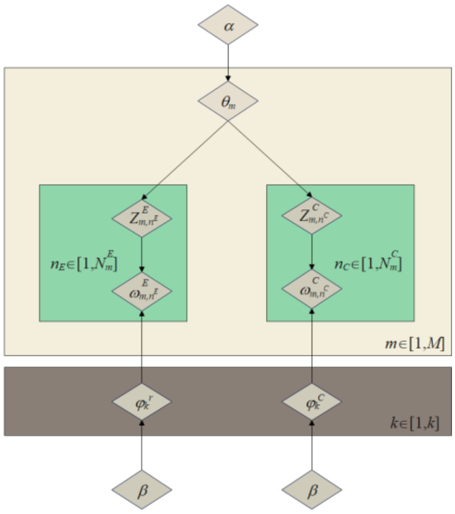


Figure 3 Bilingual LDA model diagram

The paper uses Gibbs sampling algorithm to solve the two most important parameters in the LDA model: the probability distribution of terms under each topic is φ_{k}^{C} and φ_{k}^{E}, and the topic probability distribution of each text is θ_{m}.

The values of term probability distribution and topic probability distribution are obtained, and the calculation formula is as follows:

$$\varphi_{k,t} = \frac{n_{k}^{v} + \beta_{v}}{\sum_{v=1}^{V}\left(n_{k}^{v} + \beta_{v}\right)} \quad (16)$$

$$\theta_{m,k} = \frac{n_{m}^{k} + \alpha_{k}}{\sum_{k=1}^{K}\left(n_{m}^{k} + \alpha_{k}\right)} \quad (17)$$

The bilingual LDA model first converts the comparable corpus into a document-word vector matrix. It is generally based on the bag-of-words model to directly count the word frequency for conversion, but the direct use of word frequency will lead to high frequency of some common words. But these words have very low representative significance to the text. This paper analyzes the characteristics of the standardized text of talent evaluation system requirements, and standardizes the problems of sparse features and incomplete content description in the text. In order to reduce the influence of high-frequency common words and ensure the correct meaning of the required text as much as possible, this paper proposes a bilingual LDA model that combines word features. It uses the method of term frequency–inverse document frequency (TF-IDF) combined with word position features to calculate word weights to obtain word vector distribution that is more representative of text.

TF stands for word frequency, which calculates the ability of words to describe the content of documents; IDF stands for inverse document frequency, which is used to calculate the ability of words to distinguish documents. Therefore, the word frequency TF is used to represent the characteristics of similar texts.

$$tfidf_w = \frac{N_w}{N} * \left(log \frac{D+1}{D_w+1} + 1 \right) \quad (18)$$

Combined with the previous survey data, the degree of correlation between the title and the text content in academic articles is 98%, and the probability of the sentence related to the topic is in the first sentence is 75%. Therefore, the position weights of words in the paper are set as shown in formula (19):

$$p_w = \begin{cases} 0.98, w \in T \\ 0.75, w \in B \\ 0.51, w \in O \end{cases} \quad (19)$$

The formula for calculating the weight σ_w of the word w that combines the above two features is as follows:

$$\sigma_w = 0.5 * tfid_w + 0.5 * p_w \quad (20)$$

2.3 Difference comparison of system requirements specification

Figure 4 shows the process of comparing the requirements and specifications of the talent evaluation system.

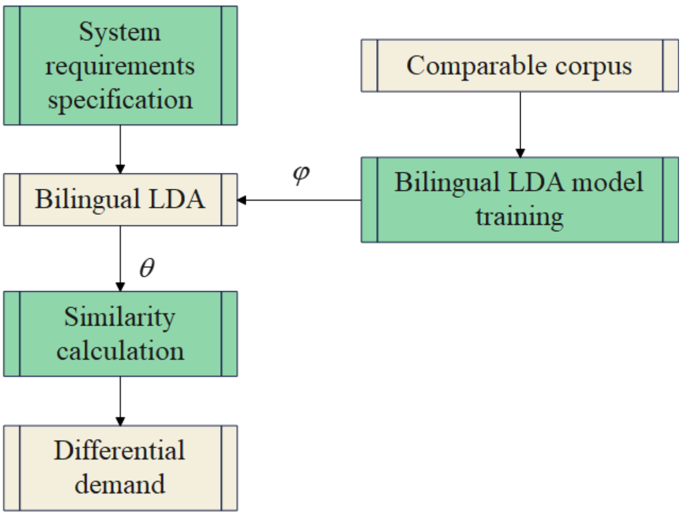


Figure 4 Framework of the SRS alignment method

First, the bilingual LDA model is trained using comparable corpus, and the training parameters are set as: α=50/K, β=0.01, and the number of iterations is 1000. In order to select the optimal K value, Perliexity is introduced here to measure the quality of the model under different K values. Formula (21) is the definition of perplexity:

$$perplexity(D_{test}) = exp\left\{-\frac{\sum_{d=1}^{M} log\, p(w_d)}{\sum_{d=1}^{M} N_d}\right\}$$
$$= exp\left\{-\frac{\sum_{d=1}^{M}\sum_{w_i \in d} log\left\{\sum_{z \in d} p(z \mid d)p(w_i \mid z)\right\}}{\sum_{d=1}^{M} N_d}\right\} \quad (21)$$

Among them, w_d is all the words in the d-th document. The smaller the value of perplexity, the better the model.

In the interval [1,400], the paper conducts experiments in increments of 10, and compares it with the bilingual LDA that does not fuse word features. The experimental results are shown in Figure 5. When the number of topics K is about 200, the perplexity value of the bilingual LDA model with the final fusion word feature is close to the minimum. The overall perplexity value of the bilingual LDA model fused with word features is lower than that of the unfused bilingual LDA model. When the number of topics is about 150, the model gradually converges, the perplexity value tends to be the lowest, and the stability of the converged model is higher. Therefore, the number of topics selected for the paper is K=150.

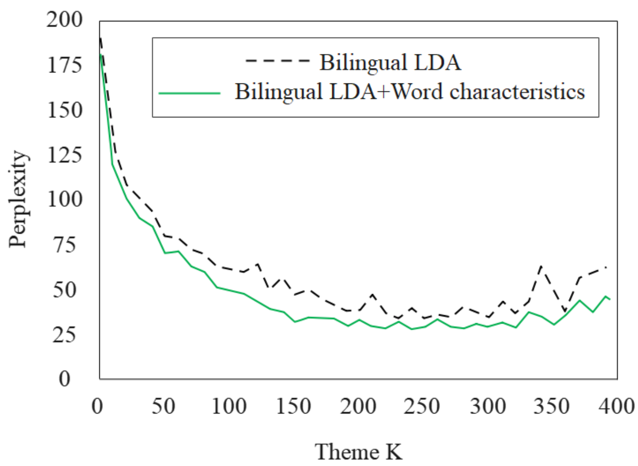


Figure 5 The perplexity of the model under different K values

The bilingual LDA model can project texts in both Chinese and English into the same topic space. Table 1 lists the topic-term distribution generated by the bilingual LDA model after training, and selects the top 10 terms in each topic. The topic-term distribution in the table is the result of the model output, and the first value of each tuple is the topic number. Moreover, the numerical value in front of each term is the probability that the corresponding word appears in the topic, and the words are arranged in the order of probability. The results of topic-term distribution show that these terms better represent the domain knowledge of the corresponding topic, and can roughly determine the relevant content of each topic.

The source language and target language texts get the text-topic distribution of the two texts through the trained bilingual LDA model. As shown in Figure 6, two texts are randomly selected for topic distribution calculation.

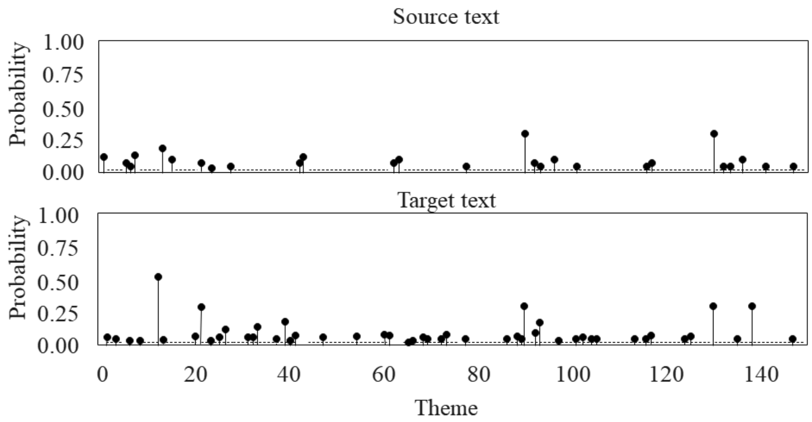


Figure 6 Document-topic distribution

3 College student talent evaluation model based on big data technology

Figure 7 shows the overall construction target diagram of the system.

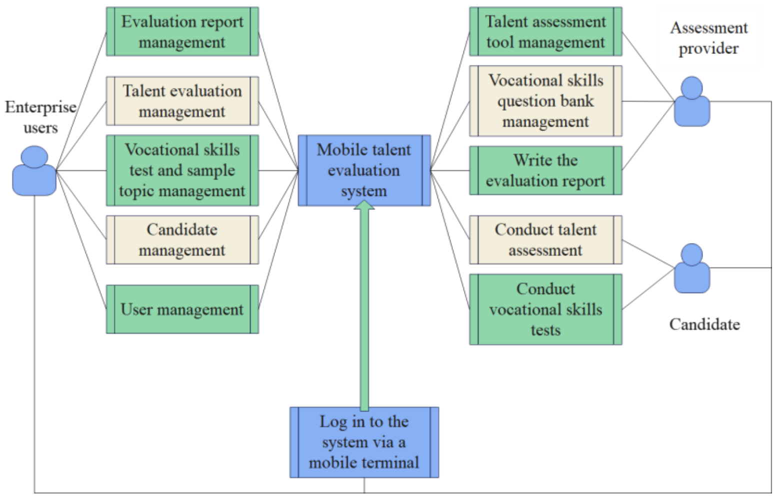


Figure 7 The overall construction target diagram of the system

The system is generally divided into six layers: the interface layer, the WebService data publishing layer, the business service layer of the Spring.NET framework, the interface interaction component layer, the basic software service layer, and the infrastructure layer, as shown in Figure 8.

Journal of Harbin Engineering University
ISSN: 1006-7043

Vol 44 No. 10
October 2023

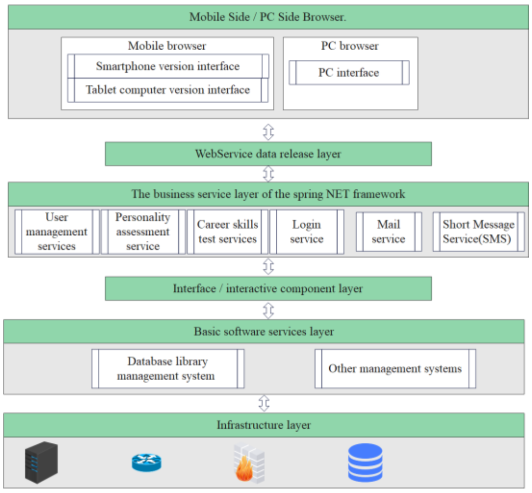
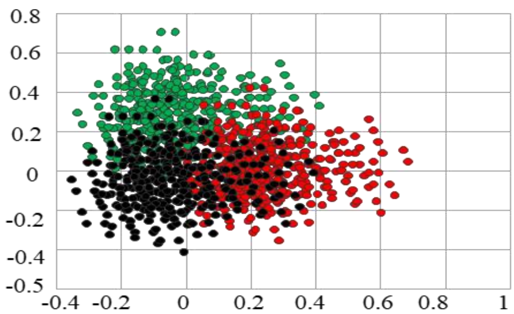
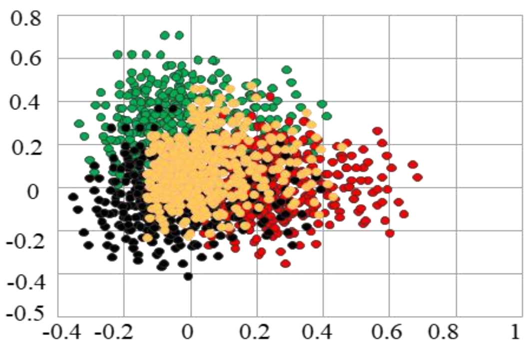


Figure 8 System overall structure diagram

To demonstrate the impact of removing boundary points on the computation of metrics for overlapping datasets, a highly overlapping dataset consisting of three blob classes is used. The sample distribution of this dataset is shown in Figure 9(a), and it can be seen that the degree of overlap between samples is very high, which is rarely encountered in clustering datasets. However, after the data set is reduced to a certain extent, the red sample points in Figure 9(b) are left. Obviously, the reduction result can highlight the core of the three classes in the data set, and strengthen the separation of classes to a certain extent.



(a) Original dataset



(b) Results after reduction

Figure 9 Sample distribution of highly overlapping datasets

The effect of the college student talent evaluation model proposed in this paper is verified to verify the effect of the model in the evaluation of students' talents, and the evaluation results shown in Table 1 are obtained.

Table 1 Verification of the effect of college student talent evaluation model based on big data technology

NO.	Personnel assessment	NO.	Personnel assessment	NO.	Personnel assessment
1	86.22	26	87.48	51	87.35
2	84.38	27	87.04	52	86.52
3	89.93	28	90.70	53	88.04
4	86.79	29	83.21	54	89.42
5	84.15	30	87.47	55	85.40
6	83.59	31	88.33	56	86.28
7	88.94	32	86.89	57	85.38
8	86.74	33	87.07	58	90.55
9	89.68	34	86.60	59	86.99
10	83.74	35	83.88	60	90.05
11	90.78	36	83.10	61	85.39
12	83.17	37	90.18	62	83.29
13	87.90	38	88.53	63	88.85
14	85.68	39	90.05	64	85.30
15	89.76	40	87.42	65	90.69
16	85.53	41	90.13	66	83.81
17	83.23	42	88.73	67	87.92
18	84.81	43	84.08	68	83.26
19	85.49	44	86.92	69	84.74
20	89.80	45	88.48	70	90.49
21	83.23	46	88.50	71	86.69
22	90.05	47	85.82	72	86.38
23	90.42	48	86.34	73	86.70

24	84.12	49	90.46	74	88.58
25	88.86	50	83.12	75	87.30

From the above analysis, we can see that the college student talent evaluation model based on big data technology proposed in this paper can effectively improve the effect of college student talent evaluation.

4 Conclusion

Talents are becoming more and more important to enterprises, and enterprises have to invest a lot of manpower and material resources every year to recruit suitable talents. How to recruit suitable talents quickly and effectively is an important issue facing enterprises. The introduction of talent evaluation in the recruitment process is an effective means to save recruitment costs and improve recruitment efficiency. The process of constructing the use case model and the user interface prototype is an iterative process. During the iteration, it constantly interacts with the user and modifies the model and the interface prototype according to the user's feedback information. This paper combines big data technology to build a college student talent evaluation model, which provides a reference for schools to better cultivate talents, and also provides a channel for the society to select talents. The experimental analysis shows that the college student talent evaluation model based on big data technology proposed in this paper can effectively improve the effect of college student talent evaluation.

References

[1] Alayoubi, M. M., Al Shobaki, M. J., & Abu-Naser, S. S. (2020). Strategic leadership practices and their relationship to improving the quality of educational service in Palestinian Universities. *International Journal of Business Marketing and Management (IJBMM)*, *5*(3), 11-26.

[2] Cheng, X., Su, L., & Zarifis, A. (2019). Designing a talents training model for cross-border e-commerce: a mixed approach of problem-based learning with social media. *Electronic Commerce Research*, *19*(4), 801-822.

[3] Clark, M. E., McEwan, K., & Christie, C. J. (2019). The effectiveness of constraints-led training on skill development in interceptive sports: A systematic review. *International Journal of Sports Science & Coaching*, *14*(2), 229-240.

[4] Rasca, L. (2018). Employee experience-an answer to the deficit of talents, in the fourth industrial revolution. *Calitatea*, *19*(S3), 9-14.

[5] Kolman, N. S., Kramer, T., Elferink-Gemser, M. T., Huijgen, B. C., & Visscher, C. (2019). Technical and tactical skills related to performance levels in tennis: A systematic review. *Journal of sports sciences*, *37*(1), 108-121.

[6] Smirnova, Z. V., Zanfir, L. N., Vaganova, O. I., Bystrova, N. V., Frolova, N. V., & Maseleno, A. (2018). WorldSkills as means of improving quality of pedagogical staff training. *International Journal of Engineering and Technology (UAE)*, *7*(4), 4103-4108.

[7] Sarmento, H., Anguera, M. T., Pereira, A., & Araújo, D. (2018). Talent identification and development in male football: a systematic review. *Sports medicine*, *48*(4), 907-931.

[8] Bennett, K. J., Vaeyens, R., & Fransen, J. (2019). Creating a framework for talent identification and development in emerging football nations.

Science and Medicine in Football, *3*(1), 36-42.

[9] Elferink-Gemser, M. T., & Hettinga, F. J. (2017). Pacing and self-regulation: important skills for talent development in endurance sports. *International journal of sports physiology and performance*, *12*(6), 831-835.

[10] Issurin, V. B. (2017). Evidence-based prerequisites and precursors of athletic talent: a review. *Sports Medicine*, *47*(10), 1993-2010.

[11] Paposa, K. K., & Kumar, Y. M. (2019). Impact of training and development practices on job satisfaction: A study on faculty members of technical education institutes. *Management and Labour Studies*, *44*(3), 248-262.

[12] Ali, N. A. M., & Kasim, N. (2019). Talent management for Shariah auditors: case study evidence from the practitioners. *International Journal of Financial Research*, *10*(3), 252-266.

[13] Rodriguez, J., & Walters, K. (2017). The importance of training and development in employee performance and evaluation. *World Wide Journal of Multidisciplinary Research and Development*, *3*(10), 206-212.

[14] Semenova, L. V., Zaitseva, N. A., Rodinova, N. P., Glagoleva, L. E., Fursov, V. A., Radina, O. I., & Tsutsulyan, S. V. (2018). Improving the training of personnel based on the model of interaction between educational organizations and centers for assessing qualifications. *Modern journal of language teaching methods*, *8*(3), 356-368.

[15] Dawi, A. H., Idris, I., Lambin, R., & Ibrahim, A. B. (2019). Preliminary Study on the Implementation of National Human Development Coaching in Malaysian Skills Diploma. *International Journal of Academic Research in Business and Social Sciences*, *9*(9), 798-810.

[16] Dash, D., Farooq, R., Panda, J. S., & Sandhyavani, K. V. (2019). Internet of Things (IoT): the new paradigm of HRM and skill development in the fourth industrial revolution (industry 4.0). *IUP Journal of Information Technology*, *15*(4), 7-30.

[17] Tri, N. M., Hoang, P. D., & Dung, N. T. (2021). Impact of the industrial revolution 4.0 on higher education in Vietnam: challenges and opportunities. *Linguistics and Culture Review*, *5*(S3), 1-15.

[18] Anufrieva, N. I., & Tsarev, D. V. (2017). Methodological foundations for the artistic performance competence formation of the music students in the educational environment of a university. *Contemporary Problems of Social Work*, *3*(3), 15-23.